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REALLY UNCERTAIN BUSINESS CYCLES

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We investigate the role of uncertainty in business cycles. First, we demonstrate that microeconomic uncertainty rises sharply during recessions, including during the Great Recession of 2007–2009. Second, we show that uncertainty shocks can generate drops in gross domestic product of around 2.5% in a dynamic stochastic general equilibrium model with heterogeneous firms. However, we also find that uncertainty shocks need to be supplemented by first-moment shocks to fit consumption over the cycle. So our data and simulations suggest recessions are best modelled as being driven by shocks with a negative first moment and a positive second moment. Finally, we show that increased uncertainty can make first-moment policies, like wage subsidies, temporarily less effective because firms become more cautious in responding to price changes.

KEYWORDS: Uncertainty, adjustment costs, business cycles.

1. INTRODUCTION

UNCERTAINTY has received substantial attention recently. For example, the Federal Open Market Committee minutes repeatedly emphasize uncertainty as a key factor in the 2001 and 2007–2009 recessions. This paper seeks to evaluate the role of uncertainty for business cycles in two parts. In the first part, we develop new empirical measures of uncertainty using detailed Census microdata from 1972–2011 and we highlight three main results. First, the dispersion of plant-level innovations to their total factor productivity (TFP) is strongly countercyclical, rising steeply in recessions. For example, Figure 1 shows the dispersion of TFP shocks for a balanced panel of plants during the 2 years before the Great Recession (2005–2006) and 2 years during the recession (2008–2009). We find

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Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. We thank our editor Lars Hansen, our anonymous referees, our formal discussants Sami Alpanda, Eduardo Engel, Frank Smets, Eric Swanson, and Iván Alfaro, as well as Angela Andrus at the RDC and numerous seminar audiences for comments.

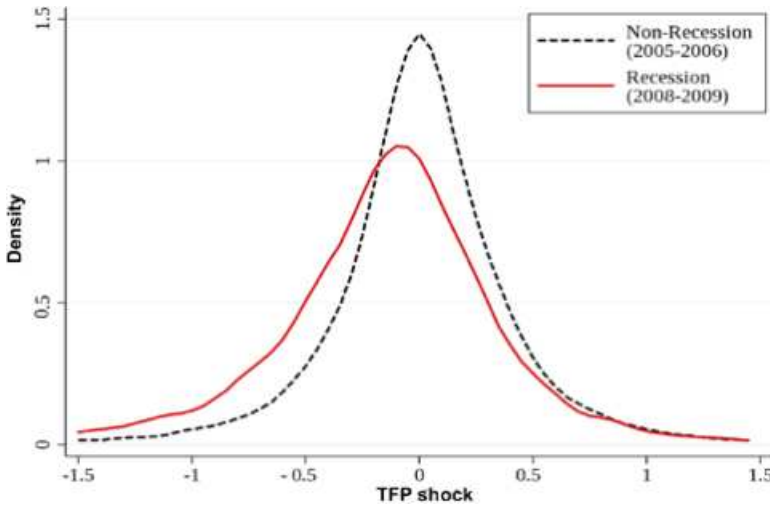


FIGURE 1.—The variance of establishment-level TFP shocks increased by 76% in the Great Recession. Notes: Constructed from the Census of Manufactures and the Annual Survey of Manufactures using a balanced panel of 15,752 establishments active in 2005–2006 and 2008–2009. TFP Shocks are defined as residuals from a plant-level $\log(\text{TFP})$ AR(1) regression that also includes plant and year fixed effects. Moments of the distribution for non-recession (recession) years are: mean 0 (–0.166), variance 0.198 (0.349), coefficient of skewness –1.060 (–1.340) and kurtosis 15.01 (11.96). The year 2007 is omitted because according to the NBER the recession began in 12/2007, so 2007 is not a clean “before” or “during” recession year.

that plant-level TFP shocks increased in variance by 76% during the recession. Similarly, Figure 2 shows that the dispersion of output growth for these same establishments increased even more, rising by a striking 152% during the recession. Thus, as Figures 1 and 2 suggest, recessions appear to be characterized by a negative first-moment and a positive second-moment shock to the establishment-level driving processes.

Our second empirical finding is that uncertainty is also strongly countercyclical at the industry level. That is, at the Standard Industrial Classification (SIC) four-digit industry level, the yearly growth rate of output is negatively correlated with the dispersion of TFP shocks to establishments within the industry. Hence, both at the industry and at the aggregate level, periods of low growth rates of output are also characterized by increased cross-sectional dispersion of TFP shocks.

Our third empirical finding is that for plants owned by publicly traded Compustat parent firms, the size of their plant-level TFP shocks is positively correlated with their parents’ daily stock returns. Hence, daily stock returns volatility—a popular high-frequency financial measure of uncertainty that also rises in recessions—is tightly linked to the size of yearly plant TFP shocks.

Given this empirical evidence that uncertainty appears to rise sharply in recessions, in the second part of the paper we build a dynamic stochastic general equilibrium (DSGE) model. Various features of the model are specified to conform as closely as possible to the standard frictionless real business cycle (RBC) model as this greatly simplifies comparison with existing work. We deviate from this benchmark in three ways. First, uncertainty is time-varying, so the model includes shocks to both the level of technology (the first moment) and its variance (the second moment) at both the microeconomic and macroeconomic levels. Second, there are heterogeneous firms that are subject to idiosyncratic shocks. Third, the model contains nonconvex adjustment costs in both capital and labor.

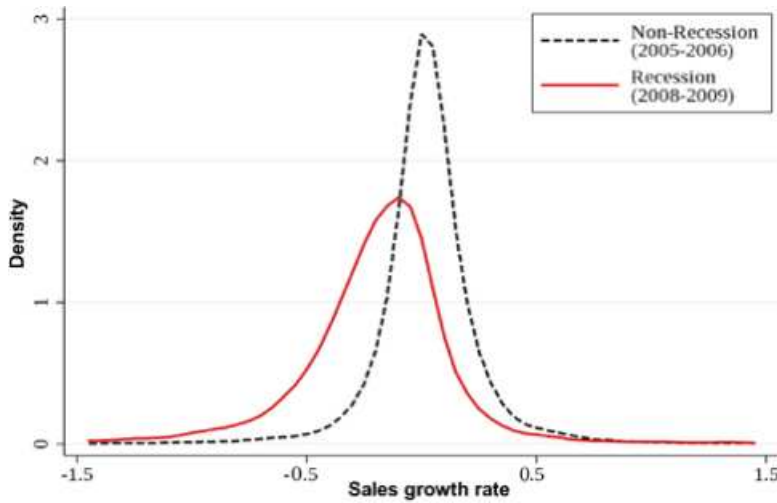


FIGURE 2.—The variance of establishment-level sales growth rates increased by 152% in the Great Recession. Notes: Constructed from the Census of Manufactures and the Annual Survey of Manufactures using a balanced panel of 15,752 establishments active in 2005–2006 and 2008–2009. Moments of the distribution for non-recession (recession) years are: mean 0.026 (−0.191), variance 0.052 (0.131), coefficient of skewness 0.164 (−0.330) and kurtosis 13.07 (7.66). The year 2007 is omitted because according to the NBER the recession began in 12/2007, so 2007 is not a clean “before” or “during” recession year.

The nonconvexities together with time variation in uncertainty imply that firms become more cautious in investing and hiring when uncertainty increases.

The model is numerically solved and estimated using macro- and plant-level data via a simulated method of moments (SMM) approach. Our SMM parameter estimates suggest that micro- and macro-uncertainty increase by around threefold during recessions.

Simulations of the model allow us to study its response to an uncertainty shock. Increased uncertainty makes it optimal for firms to wait, leading to significant falls in hiring, investment, and output. In our model, overall, uncertainty shocks generate a drop in gross domestic product (GDP) of around 2.5%. Moreover, the increased uncertainty reduces productivity growth. This reduction occurs because uncertainty reduces the degree of reallocation in the economy since productive plants pause expanding and unproductive plants pause contracting. The importance of reallocation for aggregate productivity growth matches empirical evidence in the United States. See, for example, [Foster, Haltiwanger, and Krizan \(2000, 2006\)](#), who report that reallocation broadly defined accounts for around 50% of manufacturing and 80% of retail productivity growth in the United States.

We then build on our theoretical model to investigate the effects of uncertainty on policy effectiveness. We use a simple illustrative example to show how time-varying uncertainty initially dampens the effect of an expansionary policy. The key to this policy ineffectiveness is that a rise in uncertainty makes firms cautious in responding to any stimulus.

Our work is related to several strands in the literature. First, we add to the extensive literature building on the DSGE framework that studies the role of TFP shocks in causing business cycles. In this literature, recessions are generally caused by large negative technology shocks (e.g., [King and Rebelo \(1999\)](#)). The reliance on negative technology shocks has proven to be controversial, as it suggests that recessions are times of techno-

logical regress. As discussed above, our work provides a rationale for at least some portion of variation in measured productivity. Countercyclical increases in uncertainty lead to a freeze in economic activity, substantially lowering productivity growth during recessions.

Second, the paper relates to the literature on investment under uncertainty. A rapidly growing body of work has shown that uncertainty can directly influence firm-level investment and employment in the presence of adjustment costs. Recently, the literature has started to focus on stochastic volatility and its impacts on the economy.¹ Finally, the paper also builds upon a recent literature that studies the role of microeconomic rigidities in general equilibrium macromodels.²

The remainder of this paper is organized as follows. Section 2 discusses the empirical behavior of uncertainty over the business cycle. In Section 3, we formally present the DSGE model, define the recursive equilibrium, and present our nonlinear solution algorithm. We discuss the estimation of parameters governing the uncertainty process in Section 4, while in Section 5, we study the impact of uncertainty shocks on the aggregate economy. Section 6 studies the implications for government policy in the presence of time-varying uncertainty. Section 7 concludes. Appendixes in the Supplementary Material (Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018)) include details on the data (Appendix A), model solution (Appendix B), estimation (Appendix C), and a benchmark representative agent model (Appendix D).

2. MEASURING UNCERTAINTY OVER THE BUSINESS CYCLE

Before presenting our empirical results, it is useful to briefly discuss what we mean by time-varying uncertainty in the context of our model.

We assume that a firm, indexed by j , produces output in period t according to the production function

$$y_{j,t} = A_t z_{j,t} f(k_{j,t}, n_{j,t}), \quad (1)$$

where $k_{j,t}$ and $n_{j,t}$ denote idiosyncratic capital and labor employed by the firm. Each firm's productivity is a product of two separate processes: an aggregate component, A_t , and an idiosyncratic component, $z_{j,t}$.

We assume that the aggregate and idiosyncratic components of business conditions follow autoregressive (AR) processes:

$$\log(A_t) = \rho^A \log(A_{t-1}) + \sigma_{t-1}^A \varepsilon_t, \quad (2)$$

$$\log(z_{j,t}) = \rho^Z \log(z_{j,t-1}) + \sigma_{t-1}^Z \varepsilon_{j,t}. \quad (3)$$

¹For a focus on the firm level, see Bernanke (1983), Romer (1990), Bertola and Caballero (1994), Dixit and Pindyck (1994), Abel and Eberly (1996), Hassler (1996), and Caballero and Engel (1999). For a macro-focus, see Bloom's (2009) partial equilibrium model with stochastic volatility, Fernandez-Villaverde, Guerron-Quintana, Rubio-Ramirez, and Uribe's (2011) paper on uncertainty and real exchange rates, Kehrig's (2015) paper on countercyclical productivity dispersion, Christiano, Motto, and Rostagno's (2014), Arellano, Bai, and Kehoe's (2012), and Gilchrist, Sim, and Zakrajsek's (2014) papers on uncertainty shocks in models with financial constraints, Basu and Bundick's (2016) paper on uncertainty shocks in a new-Keynesian model, Fernandez-Villaverde, Guerron-Quintana, Kuester, and Rubio-Ramirez's (2015) paper on fiscal policy uncertainty, and Bachmann and Bayer's (2013, 2014) papers on microlevel uncertainty with capital adjustment costs.

²See, for example, Hopenhayn and Rogerson (1993), Thomas (2002), Veracierto (2002), Gourio and Kashyap (2007), Khan and Thomas (2008, 2013), Bachmann, Caballero, and Engel (2013), House (2014), or Winberry (2016).

We allow the variance of innovations, σ_t^A and σ_t^Z , to move over time according to two-state Markov chains, generating periods of low and high macro- and micro-uncertainty.

There are two assumptions embedded in this formulation. First, the volatility in the idiosyncratic component, $z_{j,t}$, implies that productivity dispersion *across* firms is time-varying, while volatility in the aggregate component, A_t , implies that *all* firms are affected by more volatile shocks. Second, given the timing assumption in (2) and (3), firms learn in advance that the distribution of shocks from which they will draw in the next period is changing. This timing assumption captures the notion of uncertainty that firms face about future business conditions.

These two shocks are driven by different statistics. Volatility in $z_{j,t}$ implies that cross-sectional dispersion-based measures of firm performance (output, sales, stock market returns, etc.) are time-varying, while volatility in A_t induces higher variability in aggregate variables like GDP growth and the Standard and Poor's 500 index. Next we turn to our cross-sectional and macroeconomic uncertainty measures, detailing how both appear to rise in recessions.

2.1. Microeconomic Uncertainty Over the Business Cycle

In this section we present a set of results showing that shocks at the *establishment*-level, *firm*-level, and *industry*-level all increase in variance during recessions. In our model in Section 3 we focus on units of production, ignoring multi-establishment firms or industry-level shocks to reduce computational burden. Nevertheless, we present data at these three different levels to demonstrate the generality of the increase in idiosyncratic shocks during recessions.

Our first set of measures comes from the Census panel of manufacturing establishments. In summary, with extensive details in Appendix A, this data set contains detailed output and input data on over 50,000 establishments from 1972 to 2011. We focus on the subset of 15,673 establishments with 25+ years of data to ensure that compositional changes do not bias our results, generating a sample of almost half a million establishment-year observations.

To measure uncertainty, we first calculate establishment-level TFP ($\hat{z}_{j,t}$) using the standard approach from Foster, Haltiwanger, and Krizan (2000). We then define TFP shocks ($e_{j,t}$) as the residual from the first-order autoregressive equation for establishment-level log TFP,

$$\log(\hat{z}_{j,t}) = \rho \log(\hat{z}_{j,t-1}) + \mu_j + \lambda_t + e_{j,t}, \quad (4)$$

where μ_j is an establishment-level fixed effect (to control for permanent establishment-level differences) and λ_t is a year fixed effect (to control for cyclical shocks). Since this residual also contains plant-level demand shocks that are not controlled for by four-digit price deflators (see Foster, Haltiwanger, and Syverson (2008)), our revenue-based measure will combine both TFP and demand shocks.

Finally, we define microeconomic uncertainty, $\sigma_{t-1}^{\hat{z}}$, as the cross-sectional dispersion of $e_{j,t}$ calculated on a yearly basis. In Figure 3, we depict the interquartile range (IQR) of this TFP shock within each year. As Figure 3 shows, the series exhibits a clearly countercyclical behavior. This is particularly striking for the recent Great Recession of 2007–2009, which displays the highest value of TFP dispersion since the series began in 1972.

Table I more systematically evaluates the relationship between the dispersion of TFP shocks and recessions. In column 1, we regress the cross-sectional standard deviation (S.D.) of establishment TFP shocks on an indicator for the number of quarters in a recession during that year. So, for example, this variable has a value of 0.25 in 2007 as the

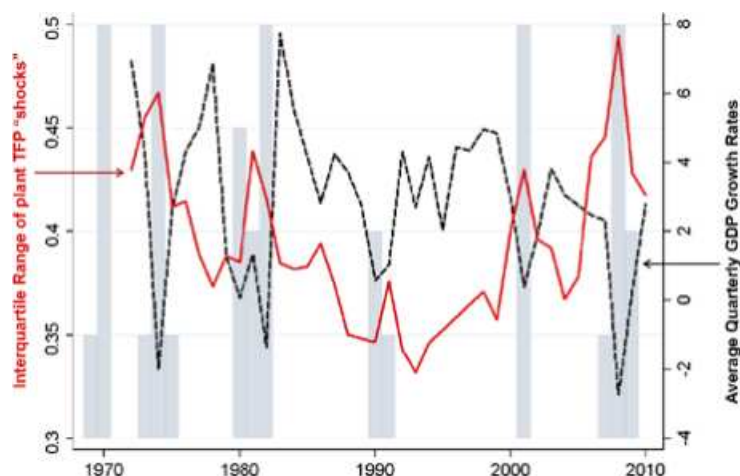


FIGURE 3.—TFP “shocks” are more dispersed in recessions. Notes: Constructed from the Census of Manufactures and the Annual Survey of Manufactures establishments, using establishments with 25+ years to address sample selection. Grey shaded columns are the share of quarters in recession within a year.

recession started in quarter IV, and values of 1 and 0.5 in 2008 and 2009, respectively, as the recession continued until quarter II in 2009. We find a coefficient of 0.064, which is highly significant (a t -statistic of 6.9). Given that the mean of the S.D. of establishment TFP shocks is 0.503, a year in recession is associated with a 13% increase in the dispersion of TFP shocks. In the bottom panel, we report that this S.D. of establishment TFP shocks also has a highly significant correlation with GDP growth of -0.45 .

Our finding here of countercyclical dispersion of microlevel outcomes mirrors a range of other recent papers such as [Bachmann and Bayer \(2014\)](#) in German data, [Kehrig \(2015\)](#) in a similar sample of U.S. Census data, or [Jurado, Ludvigson, and Ng \(2014\)](#), [Vavra \(2014\)](#), and [Berger and Vavra \(2015\)](#) for different samples of U.S. firms. A number of these papers build alternative theories or interpretations of such patterns in the microdata qualitatively distinct from our own, but the core empirical regularity of countercyclical microlevel dispersion is remarkably robust.

In columns 2 and 3, we examine the coefficient of skewness and kurtosis of TFP shocks over the cycle and, interestingly, find no significant correlations.³ This suggests that recessions can be characterized at the microeconomic level as a negative first-moment shock plus a positive second-moment shock. In column 4, we use an outlier-robust measure of cross-sectional dispersion, which is the IQR range of TFP shocks, and again find this rises significantly in recessions. The point estimate on recession of 0.061 implies an increase of over 15% in the IQR of TFP shocks in a recession year.⁴ In column 5, as another robust-

³This lack of significant correlation was robust in a number of experiments we ran. For example, if we drop the time trend and Census survey year controls, the result in column 1 on the standard deviation remains highly significant at 0.062 (0.020), while the results in columns 2 and 3 on skewness and kurtosis remain insignificant at -0.250 (0.243) and -0.771 (2.755). We also experimented with changing the establishment selection rules (keeping those with 2+ or 38+ years rather than 25+ years) and again found the results robust, as shown in Appendix Table A1. Interestingly, [Guvenen, Ozkan, and Song \(2014\)](#) find an increase in left-skewness for personal income growth during recessions, which may be absent in plant data because large negative draws lead plants to exit. Because the drop in the left tail is the key driver of recessions in our model (the “bad news principle” highlighted by [Bernanke \(1983\)](#)), this distinction is relatively unimportant.

⁴While 15% is a large increase in dispersion, it still greatly understates the increase in uncertainty in recession, because a large share of the dispersion of TFP is associated with measurement error. We formally address

TABLE I
UNCERTAINTY IS HIGHER DURING RECESSIONS^a

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	S.D. of log(TFP) shock	Skewness of log(TFP) shock	Kurtosis of log(TFP) shock	IQR of log(TFP) shock	IQR of output growth	IQR of sales growth	IQR of stock returns	IQR of industrial prod. growth
Sample:	Plants (manufact.)	Plants (manufact.)	Plants (manufact.)	Plants (manufact.)	Plants (manufact.)	Public firms (all sectors)	Public firms (all sectors)	Industries (manufact.)
Recession	0.064*** (0.009)	−0.248 (0.191)	−1.334 (1.994)	0.061*** (0.019)	0.077*** (0.019)	0.032*** (0.007)	0.025*** (0.003)	0.044*** (0.004)
Mean of dep. var.	0.503	−1.525	20.293	0.395	0.196	0.186	0.104	0.101
Corr. GDP growth	−0.450***	0.143	0.044	−0.444***	−0.566***	−0.275***	−0.297***	−0.335***
Frequency	Annual	Annual	Annual	Annual	Annual	Quarterly	Monthly	Monthly
Years	1972–2011	1972–2011	1972–2011	1972–2011	1972–2011	1962:1–2010:3	1960–2010	1972–2010
Observations	39	39	39	39	39	191	609	455
Underlying sample	461,232	461,232	461,232	461,232	461,232	320,306	931,143	70,487

^aEach column reports a time-series ordinary least squares (OLS) regression point estimate (and standard error below in parentheses) of a measure of uncertainty on a recession indicator. The recession indicator is the share of quarters in that year in a recession in columns 1–5, whether that quarter was in a recession in column 6, and whether the month was in recession in columns 7 and 8. Recessions are defined using the National Bureau of Economic Research (NBER) data. In the bottom panel we report the mean of the dependent variable and its correlation with real GDP growth. In columns 1–5, the sample is the population of manufacturing establishments with 25 years or more of observations in the Annual Survey of Manufactures (ASM) or Census of Manufactures (CM) survey between 1972 and 2009, which contains data on 15,673 establishments across 40 years of data (one more year than the 39 years of regression data since we need lagged TFP to generate a TFP shock measure). We include plants with 25+ years to reduce concerns over changing samples. In column 1, the dependent variable is the cross-sectional standard deviation (S.D.) of the establishment-level shock to total factor productivity (TFP). This shock is calculated as the residual from the regression of log(TFP) at year $t + 1$ on its lagged value (year t), a full set of year dummies, and establishment fixed effects. In column 2, we use the cross-sectional coefficient of skewness of the TFP shock, in column 3, the cross-sectional coefficient of kurtosis, and in column 4, the cross-sectional interquartile range of this TFP shock as an outlier robust measure. In column 5, the dependent variable is the interquartile range of plants' sales growth. In column 6, the dependent variable is the interquartile range of firms' sales growth by quarter for all public firms with 25 years (100 quarters) or more in Compustat between 1962 and 2010. In column 7, the dependent variable is the within firm-quarter interquartile range of firms' monthly stock returns for all public firms with 25 years (300 months) or more in Center for Research in Security Prices (CRSP) between 1960 and 2010. Finally, in column 8, the dependent variable is the interquartile range of industrial production growth by month for manufacturing industries from the Federal Reserve Board's monthly industrial production database. All regressions include a time trend and for columns 1–5 Census year dummies (for Census year and for three lags). Robust standard errors are applied in all columns to control for any potential serial correlation. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance. Results are also robust to using Newey–West corrections for the standard errors. Data are available at <http://www.stanford.edu/~nbloom/RUBC.zip>.

ness test, we use plant-level output growth, rather than TFP shocks, and find a significant rise in recessions. We also run a range of other experiments on different indicators, measures of TFP, and samples, and always find that dispersion rises significantly in recessions.⁵ For example, Figure A1 plots the correlation of plant TFP rankings between consecutive years. This shows that during recessions these rankings churn much more, as increased microeconomic variance leads plants to change their position within their industry-level TFP rankings more rapidly.

In column 6, we use a different data set that is the sample of all Compustat firms with 25+ years of data. This has the downside of being a much smaller selected sample containing only 2465 publicly quoted firms, but spanning all sectors of the economy, and providing quarterly sales observations going back to 1962. We find that the quarterly dispersion of sales growth in this Compustat sample is also significantly higher in recessions.

One important caveat when using the variance of productivity “shocks” to measure uncertainty is that the residual $e_{j,t}$ is a productivity shock only in the sense that it is unforecasted by the regression equation (4), rather than unforecasted by the establishment. We address this concern in two ways. First, in column 7 we examine the cross-sectional spread of stock returns, which reflects the volatility of news about firm performance, and again find this is countercyclical, echoing the prior results in Campbell, Lettau, Malkiel, and Xu (2001). In fact, as we discuss below in Table III, we also find that establishment-level shocks to TFP are significantly correlated to their parent’s stock returns, so that at least part of these establishment TFP shocks are new information to the market. Furthermore, to remove the forecastable component of stock returns, we repeated the specification in column 7 by first removing the quarter by firm mean of firm returns. This controls for any quarterly factors—like size, market/book value, research and development (R&D) intensity, and leverage—that may influence expected stock returns (e.g., Bekaert, Hodrick, and Zhang (2012)), although of course the influence of common factors that may vary at a higher frequency within the quarter may remain. The coefficient (standard error) on recession in these regressions is 0.019 (0.003), similar to the results obtained in column 7.

Second, we extend the TFP forecast regressions (4) to include additional observables that are likely to be informative about future TFP changes. Adding these in the regression accounts for at least some of the superior information that the establishment might have over the econometrician, helping us to back out true shocks to TFP from the perspective of the establishments. Figure 4 reports the IQR of the TFP shocks for the baseline forecast regression, as well as for three other dispersion measures, where we sequentially add more variables to the forecasting regressions that are used to recover TFP shocks. First we add two extra lags in levels and polynomials of TFP, next we also include lags and polynomials of investment, and finally we include lags and polynomials of multiple inputs including employment, energy, and materials expenditure. As is clear from the figure, even when forward looking establishment choices for investment and employment are included, the overall cyclical patterns of uncertainty are almost unchanged.

that in our SMM estimation framework. See Section 4.2 for estimates of the underlying increase in uncertainty in recession and see Appendix C for details.

⁵For example, the IQR of employment growth rates has a point estimate (standard error) of 0.051 (0.012), the IQR of TFP shocks measured using an industry-by-industry forecasting equation version of (4) has a point estimate (standard error) of 0.064 (0.019), using 2+ year samples for the S.D. of TFP shocks, we find a point estimate (standard error) of 0.046 (0.014), and using a balanced panel of 38+ year establishments, we find a point estimate (standard error) of 0.075 (0.015). Finally, the IQR of TFP shocks measured after removing firm-year means and then applying (4) has a point estimate (standard error) of 0.028 (0.011), so that dispersion of productivity shocks even across plants within firms rises within recessions.

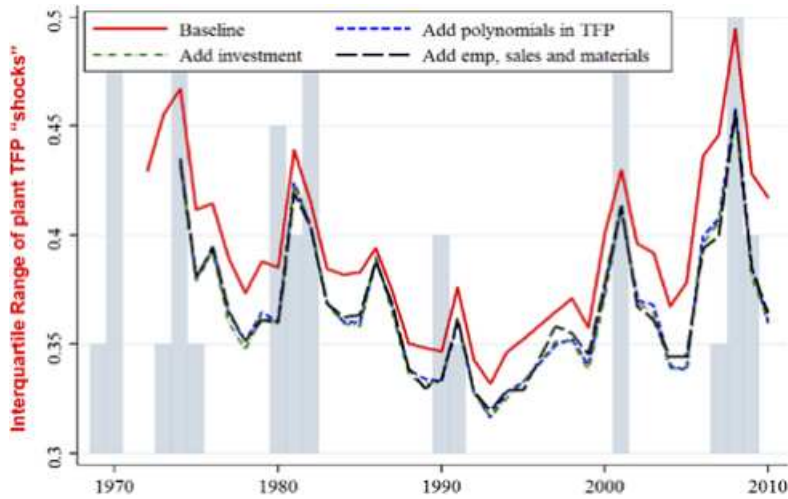


FIGURE 4.—Robustness test: different measures of TFP “shocks” are all more dispersed in recessions. Notes: Constructed from the Census of Manufactures and the Annual Survey of Manufactures establishments, using establishments with 25+ years to address sample selection. Grey shaded columns are share of quarters in recession within a year. The four lines are: *Baseline*: Interquartile Range of plant TFP “shocks” (as in Figure 3). *Add polynomials in TFP*: includes the first, second and third lags of log TFP, and their degree 5 polynomials in the AR regression which is used to recover TFP shocks. *Add investment*: includes all the controls from the previous specification plus the first, second and third lags of investment rate, and their degree 5 polynomials. *Add emp, sales and materials*: includes all the controls from the previous specification plus the second and third lags of log employment, log sales, and log materials, as well as their degree 5 polynomials.

Finally, in column 8, we examine another measure of uncertainty, which is the cross-sectional spread of industry-level output growth rates, finding again that this is strongly countercyclical.

Hence, in summary plant-level (columns 1–5), firm-level (columns 6 and 7), and industry-level (column 8) measures of volatility and uncertainty all appear to be strongly countercyclical, suggesting that microeconomic uncertainty rises in recessions at all levels.

2.2. Industry Business Cycles and Uncertainty

In Table II, we report another set of results that disaggregate down to the industry level, finding a very similar result that uncertainty is significantly higher during periods of slower growth. To do this, we exploit the size of our Census data set to examine the dispersion of productivity shocks *within* each SIC four-digit industry–year cell. The size of the Census data set means that it has a mean (median) of 27.1 (17) establishments per SIC four-digit industry–year cell, which enables us to examine the link between within-industry dispersion of establishment TFP shocks and industry growth.

Table II displays a series of industry panel regressions in which our dependent variable is the IQR of TFP shocks for all establishments in each industry (i)–year (t) cell. The regression specification that we run is

$$\text{IQR}_{i,t} = a_i + b_t + \gamma \Delta y_{i,t}.$$

The explanatory variable in column (1) ($\Delta y_{i,t}$) is the median growth rate of output between t and $t + 1$ in the industry–year cell, with a full set of industry (a_i) and year (b_t)

TABLE II
UNCERTAINTY IS ALSO ROBUSTLY HIGHER AT THE INDUSTRY LEVEL DURING INDUSTRY “RECESSIONS”^a

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	IQR of establishment TFP shocks within each industry–year cell								
Specification:	Baseline	Median industry output growth	IQR of industry output growth	Median industry establishment size	IQR of industry establishment size	Median industry capital/labor ratio	IQR of industry capital/labor ratio	IQR of industry TFP spread	Industry geographic spread
Industry output growth	−0.132*** (0.021)	−0.142*** (0.021)	−0.176*** (0.047)	−0.119*** (0.024)	−0.116*** (0.022)	−0.111*** (0.034)	−0.111*** (0.030)	−0.191*** (0.041)	−0.133*** (0.028)
Interaction of industry output growth with the variable in specification row		0.822 (0.630)	0.882 (0.996)	−0.032 (0.038)	−0.033 (0.026)	−0.197 (0.292)	−0.265 (0.330)	0.123 (0.084)	0.007 (0.122)
Years	1972–2009	1972–2009	1972–2009	1972–2009	1972–2009	1972–2009	1972–2009	1972–2009	1972–2009
Observations	16,451	16,451	16,451	16,451	16,451	16,451	16,451	16,451	16,451
Underlying sample	446,051	446,051	446,051	446,051	446,051	446,051	446,051	446,051	446,051

^aEach column reports the results from an industry-by-year OLS panel regression, including a full set of industry and year fixed effects. The dependent variable in every column is the interquartile range (IQR) of establishment-level TFP shocks within each SIC four-digit industry–year cell. The regression sample is the 16,451 industry–year cells of the population of manufacturing establishments with 25 years or more of observations in the ASM or CM survey between 1972 and 2009 (which contains 446,051 underlying establishment years of data). These industry–year cells are weighted in the regression by the number of establishment observations within that cell, with the mean and median number of establishments per industry–year cell equal to 27.1 and 17, respectively. The TFP shock is calculated as the residual from the regression of $\log(\text{TFP})$ at year $t + 1$ on its lagged value (year t), a full set of year dummies, and establishment fixed effects. In column 1, the explanatory variable is the median of the establishment-level output growth in that industry–year. In columns 2–9, a second variable is also included that is an interaction of that explanatory variable with an industry-level characteristic. In columns 2 and 3, this is the median and IQR of industry-level output growth, in columns 4 and 5 this is the median and IQR of industry-level establishment size in employees, in columns 6 and 7, this is the median and IQR of industry-level capital/labor ratios, in column 8 this is the IQR of industry-level TFP levels (note the mean is zero by construction), while finally in column 9, this interaction is the dispersion of industry-level concentration measured using the Ellison–Glaeser dispersion index. Standard errors clustered by industry are reported in brackets below every point estimate. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

fixed effects also included. Column 1 of Table II shows that the within-industry dispersion of TFP shocks is significantly higher when that industry is growing more slowly. Since the regression has a full set of year and industry dummies, this is independent of the macroeconomic cycle. So at both the aggregate and the industry level, slowdowns in growth are associated with increases in the cross-sectional dispersion of shocks.

This result raises the question of why the within-industry dispersion of shocks is higher during industry slowdowns. To explore whether it is the case that industry slowdowns impact some types of establishments differently, we proceed as follows. In columns 2–9, we run a series of regressions to check whether the increase in within-industry dispersion is larger given some particular characteristics of the industry. These are regressions of the form

$$\text{IQR}_{i,t} = a_i + b_t + \gamma \Delta y_{i,t} + \delta \Delta y_{i,t} * x_i,$$

where x_i are industry characteristics (see Appendix A for details). Specifically, in column 2, we interact industry growth with the median growth rate in that industry over the full period. The rationale is that perhaps faster growing industries are more countercyclical in their dispersion? We find no relationship, suggesting long-run industry growth rates are not linked to the increase in dispersion of establishment shocks they see in recessions. Similarly, in column 3, we interact industry growth with the dispersion of industry growth rates. Perhaps industries with a wide spread of growth rates across establishments are more countercyclical in their dispersion? Again, we find no relationship. The rest of the table reports similar results for the median and dispersion of plant size within each industry (measured by the number of employees, columns 4 and 5), the median and dispersion of capital/labor ratios (columns 6 and 7), and TFP and geographical dispersion interactions (columns 8 and 9). In all of these we find insignificant coefficients on the interaction of industry growth with industry characteristics.

Thus, to summarize, it appears that, first, the within-industry dispersion of establishment TFP shocks rises sharply when the industry growth rates slow down, and, second, perhaps surprisingly, this relationship appears to be broadly robust across all industries.

An obvious question regarding the relationship between uncertainty and the business cycle is the direction of causality. Identifying the direction of causation is important in highlighting the extent to which countercyclical macro-uncertainty and industry uncertainty is a shock driving cycles versus an endogenous mechanism amplifying cycles. A recent literature has suggested a number of mechanisms for uncertainty to increase endogenously in recessions. See, for example, the papers on information collection by [Van Nieuwerburgh and Veldkamp \(2006\)](#), [Fajgelbaum, Schaal, and Tascherau-Dumouchel \(2017\)](#) or [Chamley and Gale \(1994\)](#), on experimentation in [Bachmann and Moscarini \(2011\)](#), on forecasting by [Orlik and Veldkamp \(2015\)](#), on policy uncertainty by [Lubos and Veronesi \(2013\)](#), and on search by [Petrosky-Nadeau and Wasmer \(2013\)](#). Our view is that recessions appear to be initiated by a combination of negative first- and positive second-moment shocks, with ongoing amplification and propagation from uncertainty movements. So the direction of causality likely goes in both directions, and while we model the causal impact of uncertainty in this paper, more work on the reverse (amplification) direction would also be helpful.

2.3. *Are Establishment-Level TFP Shocks a Good Proxy for Uncertainty?*

The evidence we have provided for countercyclical aggregate and industry-level uncertainty relies heavily on using the dispersion of establishment-level TFP shocks as a

measure of uncertainty. To check this, Table III compares our establishment TFP shock measure of uncertainty with other measures of uncertainty, primarily the volatility of daily and monthly firm-stock returns, which have been used commonly in the prior uncertainty literature.⁶ Importantly, we note that the goal of this section is to demonstrate the correlation between the different measures of uncertainty. Thus, this section does not imply any direction of causation.

In column 1 of Table III, we regress the mean absolute size of the TFP shock in the plants of publicly traded firms against their parent firm's within-year volatility of daily stock returns (plus a full set of firm and year fixed effects). The positive and highly significant coefficient reveals that when plants of publicly quoted firms have large (positive or negative) TFP shocks in any given year, their parent firms are likely to have significantly more volatile daily stock returns over the course of that year. This is reassuring for both our TFP shock measure of uncertainty and stock market volatility measures of uncertainty, because while neither measure is ideal, the fact that they are strongly correlated suggests that they are both proxies for an underlying measure of firm-level uncertainty. In column 2, we use monthly returns rather than daily returns and find similar results, while in column 3, following Leahy and Whited (1996), we leverage adjust the stock returns and again find similar results.⁷

In column 4, we compare instead the within-year standard deviation of firm quarterly sales growth against the absolute size of their establishment TFP shocks. We find again a strikingly significant positive coefficient, showing that firms with a wider dispersion of TFP shocks across their plants tend to have more volatile sales growth within the year. Finally, in column 5, we generate an industry-level measure of output volatility within the year by taking the standard deviation of monthly production growth, and we find that this measure is also correlated with the average absolute size of establishment-level TFP shocks within the industry in that year.

So in summary, establishment-level TFP shocks are larger when the parent firms have more volatile stock returns and sales growth within the year, and the overall industry has more volatile monthly output growth within the year. This suggests that these indicators are all picking up some type of common movement in uncertainty.

2.4. Macroeconomic Measures of Uncertainty

The results discussed so far focus on establishing the countercyclicality of idiosyncratic (establishment, firm, and industry) uncertainty. With respect to macroeconomic uncertainty, existing work has documented that this measure is also countercyclical, including, for example, Schwert (1989), Campbell et al. (2001), Engle and Rangel (2008), Jurado, Ludvigson, and Ng (2014), and Stock and Watson (2012), or the survey in Bloom (2014).

Rather than repeat this evidence here, we simply include one additional empirical measure of aggregate uncertainty, which is the conditional heteroskedasticity of aggregate productivity A_t . This is estimated using a generalized autoregressive conditional heteroskedasticity GARCH(1, 1) estimator on the Basu, Fernald, and Kimball (2006) data

⁶See, for example, Leahy and Whited (1996), Schwert (1989), Bloom, Bond, and Van Reenen (2007), and Panousi and Papanikolaou (2012).

⁷As we did in column 7 of Table I, to remove the forecastable component of stock returns, we repeat columns 1 and 3, first removing the quarter by firm mean of firm returns. After doing this the coefficient (standard error) is very similar 0.324 (0.093) for column 1 and 0.387 (0.120) for column 3, mainly because the forecastable component of stock returns explains very little of the total volatility in stock returns.

TABLE III
CROSS-SECTIONAL ESTABLISHMENT UNCERTAINTY MEASURES ARE CORRELATED WITH FIRM AND INDUSTRY TIME SERIES UNCERTAINTY MEASURES^a

Dependent variable	(1)	(2)	(3)	(4)	(5)
	Mean of establishment <i>absolute</i> (TFP shock) within firm year			Mean of establishment <i>absolute</i> (TFP shocks) within industry year	
Sample	Establishments (in manufacturing) with a parent firm in compustat			Manufacturing industries	
Regression panel dimension	Firm by year			Industry by year	
S.D. of parent daily stock returns within year	0.317*** (0.091)				
S.D. of parent monthly stock returns within year		0.275*** (0.083)			
S.D. of parent daily stock returns within year, leverage adjusted			0.381*** (0.118)		
S.D. of parent quarterly sales growth within year				0.134*** (0.029)	
S.D. of monthly industrial production within year					0.330*** (0.060)
Fixed effects and clustering	Firm	Firm	Firm	Firm	Industry
Firms/industries	1838	1838	1838	1838	466
Observations	25,302	25,302	25,302	25,302	16,406
Underlying observations	172,074	172,074	172,074	172,074	446,051

^aThe dependent variable is the mean of the absolute size of the TFP shock at the firm-year level (columns 1–4) and industry-year level (column 5). This TFP shock is calculated as the residual from the regression of $\log(\text{TFP})$ at year $t + 1$ on its lagged value (year t), a full set of year dummies, and establishment fixed effects, with the absolute size generated by turning all negative values positive. The regression sample in columns 1–4 are the 25,302 firm-year cells of the population of manufacturing establishments with 25 years or more of observations in the ASM or CM survey between 1972 and 2009 that are owned by Compustat (publicly listed) firms. This covers 172,074 underlying establishment years of data. The regression sample in column 5 is the 16,406 industry-year cells of the population of manufacturing establishments with 25 years or more of observations in the ASM or CM survey between 1972 and 2009. The explanatory variables in columns 1–3 are the annual standard deviation of the parent firm's stock returns, which are calculated using the 260 daily values in columns 1 and 3 and the 12 monthly values in column 2. For comparability of monthly and daily values, the coefficients and S.E. for the daily returns in columns 1 and 3 are divided by $\sqrt{21}$. The daily stock returns in column 3 are normalized by the $(\text{equity}/(\text{debt} + \text{equity}))$ ratio to control for leverage effects. In column 4, the explanatory variable is the standard deviation of the parent firm's quarterly sales growth. Finally, in column 5, the explanatory variable is the standard deviation of the industry's monthly industrial production data from the Federal Reserve Board. All columns have a full set of year fixed effects, with columns 1–4 also having firm fixed effects while column 5 has industry fixed effects. Standard errors clustered by firm/industry are reported in brackets below every point estimate. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

on quarterly TFP growth from 1972Q1 to 2010Q4. We find that conditional heteroskedasticity of TFP growth is strongly countercyclical, rising by 25% during recessions, which is highly significant (a t -statistic of 6.1); this series is plotted in Appendix Figure A2.

3. THE GENERAL EQUILIBRIUM MODEL

We proceed by analyzing the quantitative impact of variation in uncertainty within a DSGE model. Specifically, we consider an economy with heterogeneous firms that use capital and labor to produce a final good. Firms that adjust their capital stock and employment incur adjustment costs. As is standard in the RBC literature, firms are subject to an exogenous process for productivity. We assume that the productivity process has an aggregate and an idiosyncratic component. In addition to the standard first-moment shocks considered in the literature, we allow the second moment of the innovations to productivity to vary over time. That is, shocks to productivity can be fairly small in normal times, but become potentially large when uncertainty is high.

3.1. Firms

3.1.1. Technology

The economy is populated by a large number of heterogeneous firms that employ capital and labor to produce a single final good. We assume that each firm operates a diminishing returns to scale production function with capital and labor as the variable inputs. Specifically, a firm indexed by j produces output according to

$$y_{j,t} = A_t z_{j,t} k_{j,t}^\alpha n_{j,t}^\nu, \quad \alpha + \nu < 1. \quad (5)$$

Each firm's productivity is a product of two separate processes: aggregate productivity, A_t , and an idiosyncratic component, $z_{j,t}$. Both the macro- and firm-level components of productivity follow autoregressive processes as noted in equations (2) and (3). We allow the variance of innovations to the productivity processes, σ_t^A and σ_t^Z , to vary over time according to a two-state Markov chain.

3.1.2. Adjustment Costs

There is a wide literature that estimates labor and capital adjustment costs (e.g., Hayashi (1982), Nickell (1986), Caballero and Engel (1993), Caballero and Engel (1999), Ramey and Shapiro (2001), Hall (2004), Cooper and Haltiwanger (2006), Merz and Yashiv (2007), and Cooper, Haltiwanger, and Willis (2015)). In what follows, we incorporate all types of adjustment costs that have been estimated in Bloom (2009) to be statistically significant at the 5% level. As is well known in the literature, it is the presence of nonconvex adjustment costs that leads to a real options (wait-and-see effect) of uncertainty shocks.

Capital Law of Motion. A firm's capital stock evolves according to the standard law of motion

$$k_{j,t+1} = (1 - \delta_k)k_{j,t} + i_{j,t}, \quad (6)$$

where δ_k is the rate of capital depreciation and $i_{j,t}$ denotes investment.

Capital adjustment costs are denoted by AC_k , and they equal the sum of (i) a fixed disruption cost F^K for any investment/disinvestment and (ii) a partial irreversibility resale loss for disinvestment (i.e., the resale of capital occurs at a price that is only a share $(1 - S)$

of its purchase price). Formally,

$$AC^k = \mathbb{I}(|i| > 0)y(z, A, k, n)F^k + S|i|\mathbb{I}(i < 0). \quad (7)$$

Hours Law of Motion. The law of motion for hours worked is governed by

$$n_{j,t} = (1 - \delta_n)n_{j,t-1} + s_{j,t}, \quad (8)$$

where $s_{j,t}$ denotes the net flows into hours worked and δ_n denotes the exogenous destruction rate of hours worked (due to factors such as retirement, illness, exogenous quits, etc.).

Labor adjustment costs are denoted by AC_n in total, and they equal the sum of (i) a fixed disruption cost F^L and (ii) a linear hiring/firing cost, which is expressed as a fraction of the aggregate wage (Hw). Formally,

$$AC^n = \mathbb{I}(|s| > 0)y(z, A, k, n)F^L + |s|Hw. \quad (9)$$

Note that these adjustment costs in labor imply that $n_{j,t-1}$ is a state variable for the firm.

3.1.3. The Firm's Value Function

We denote by $V(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)$ the value function of a firm. The seven state variables are given by (i) a firm's capital stock, k , (ii) a firm's hours stock from the previous period, n_{-1} , (iii) the firm's idiosyncratic productivity, z , (iv) aggregate productivity, A , (v) the current value of macro-uncertainty, σ^A , (vi) the current value of micro-uncertainty, σ^Z , and (vii) the joint distribution of idiosyncratic productivity and firm-level capital stocks and hours worked in the last period, μ , which is defined for the space $S = R_+ \times R_+ \times R_+$.

Denoting by primes the value of next period variables, the dynamic problem of the firm consists of choosing investment and hours to maximize

$$\begin{aligned} & V(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu) \\ &= \max_{i,n} \left\{ \begin{aligned} & y - w(A, \sigma^A, \sigma^Z, \mu)n - i \\ & - AC^k(k, n_{-1}, z, k'; A, \sigma^A, \sigma^Z, \mu) - AC^n(k, n_{-1}, z, n; A, \sigma^A, \sigma^Z, \mu) \\ & + \mathbb{E}[m(A, \sigma^A, \sigma^Z, \mu; A', \sigma^{A'}, \sigma^{Z'}, \mu')V(k', n, z'; A', \sigma^{A'}, \sigma^{Z'}, \mu')] \end{aligned} \right\} \end{aligned} \quad (10)$$

given a law of motion for the joint distribution of idiosyncratic productivity, capital, and hours,

$$\mu' = \Gamma(A, \sigma^A, \sigma^Z, \mu), \quad (11)$$

and the stochastic discount factor, m , which we discuss below in Section 3.4. The term $w(A, \sigma^A, \sigma^Z, \mu)$ denotes the wage rate in the economy; $K(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)$ and $N^d(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)$ denote the policy rules associated with the firm's choice of capital for the next period and current demand for hours worked.

3.2. Households

The economy is populated by a large number of identical households that we normalize to a measure 1. Households choose paths of consumption, labor supply, and investment in firm shares to maximize lifetime utility. We use the measure ψ to denote the one-period

purchased shares in firms. The dynamic problem of the household is given by

$$W(A, \sigma^A, \sigma^Z, \mu) = \max_{\{C, N, \psi'\}} \{U(C, N) + \beta \mathbb{E}[W(A', \sigma^{A'}, \sigma^{Z'}, \mu')]\}, \quad (12)$$

subject to the law of motion for μ and a sequential budget constraint

$$\begin{aligned} C + \int q(k', n, z; A, \sigma^A, \sigma^Z, \mu) d\psi'(k', n, z) \\ \leq w(A, \sigma^A, \sigma^Z, \mu)N + \int \rho(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu) d\mu(k, n_{-1}, z). \end{aligned} \quad (13)$$

Households receive labor income as well as the sum of dividends and the resale value of their investments priced at $\rho(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)$. With these resources the household consumes and buys new shares at a price $q(k', n, z; A, \sigma^A, \sigma^Z, \mu)$ per share of the different firms in the economy. We denote by $C(\psi, A, \sigma^A, \sigma^Z, \mu)$, $N^s(\psi, A, \sigma^A, \sigma^Z, \mu)$, and $\Psi'(k', n, z; A, \sigma^A, \sigma^Z, \mu)$ the policy rules that determine current consumption, time worked, and quantities of shares purchased in firms that begin the next period with a capital stock k' and who currently employ n hours with idiosyncratic productivity z .

3.3. Recursive Competitive Equilibrium

A recursive competitive equilibrium in this economy is defined by a set of quantity functions $\{C, N^s, \Psi', K, N^d\}$, pricing functions $\{w, q, \rho, m\}$, and lifetime utility and value functions $\{W, V\}$, where V and $\{K, N^d\}$ are the value and policy functions, respectively, that solve (10), while W and $\{C, N^s, \Psi'\}$ are, respectively, the value and policy functions that solve (12). There is market clearing in asset markets

$$\mu'(k', n, z') = \int \psi'(k', n, z) f(z'|z) dz,$$

the goods market

$$\begin{aligned} C(\psi, A, \sigma^A, \sigma^Z, \mu) \\ = \int \left[Azk^\alpha N^d(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)^\nu - (K(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu) - (1 - \delta_k)k) \right] \\ d\mu(k, n_{-1}, z), \end{aligned}$$

and the labor market

$$N^s(\psi, A, \sigma^A, \sigma^Z, \mu) = \int N^d(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu) d\mu(k, n_{-1}, z).$$

Finally, the evolution of the joint distribution of z , k , and n_{-1} is consistent. That is, $\Gamma(A, \sigma^A, \sigma^Z, \mu)$ is generated by $K(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)$, $N^d(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)$, and the exogenous stochastic evolution of A , z , σ^Z and σ^A , along with the appropriate integration of firms' optimal choices of capital and hours worked given current state variables.

3.4. Sketch of the Numerical Solution

We briefly describe the solution algorithm, which heavily relies on the approach in [Khan and Thomas \(2008\)](#) and [Bachmann, Caballero, and Engel \(2013\)](#). Fuller details are laid

out in Appendix B, and the full code is available in the Supplementary Material (Bloom et al. (2018)).

The model can be simplified substantially if we combine the firm and the household problems into a single dynamic optimization problem. From the household problem, we get

$$w = -\frac{U_N(C, N)}{U_C(C, N)}, \quad (14)$$

$$m = \beta \frac{U_C(C', N')}{U_C(C, N)}, \quad (15)$$

where equation (14) is the standard optimality condition for labor supply and equation (15) is the standard expression for the stochastic discount factor. We assume that the momentary utility function for the household is separable across consumption and hours worked,

$$U(C_t, N_t) = \frac{C_t^{1-\eta}}{1-\eta} - \theta \frac{N_t^\chi}{\chi}, \quad (16)$$

implying that the wage rate is given by

$$w_t = \theta N_t^{\chi-1} C_t^\eta. \quad (17)$$

We define the intertemporal price of consumption goods as $p(A, \sigma^Z, \sigma^A, \mu) \equiv U_C(C, N)$. This then allows us to redefine the firm's problem in terms of marginal utility, denoting the new value function as $\tilde{V} \equiv pV$. The firm problem can then be expressed as

$$\begin{aligned} & \tilde{V}(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu) \\ &= \max_{\{i, n\}} \left\{ p(A, \sigma^A, \sigma^Z, \mu) (y - w(A, \sigma^A, \sigma^Z, \mu) n - i - AC^k - AC^n) \right. \\ & \quad \left. + \beta \mathbb{E}[\tilde{V}(k', n, z'; A', \sigma^{A'}, \sigma^{Z'}, \mu')] \right\}. \end{aligned} \quad (18)$$

To solve this problem, we employ nonlinear techniques that build upon Krusell and Smith (1998). Detailed discussion of the algorithm is provided in Appendix B, where we implement a range of alternative implementations of our Krusell–Smith type algorithm. Importantly, as we discuss in Appendix B, the main results remain robust across the different alternatives we consider.

4. PARAMETER VALUES

In this section, we describe the quantitative specification of our model. To maintain comparability with the RBC literature, we perform a standard calibration when possible (see Section 4.1 and Table IV). However, the parameters that govern the uncertainty process cannot be calibrated to match first moments in the U.S. data; neither have they been previously estimated in the literature. As such, we adopt a simulated method of moments (SMM) estimation procedure to choose these values in Section 4.2. In Section 5.2.3, we explore the sensitivity of the results to different parameter values.

TABLE IV
CALIBRATED MODEL PARAMETERS^a

<i>Preferences and Technology</i>		
β	0.95 ^{1/4}	Annual discount factor of 95%
η	1	Unit elasticity of intertemporal substitution (Khan and Thomas (2008))
θ	2	Leisure preference, households spend 1/3 of time working
χ	1	Infinite Frisch elasticity of labor supply (Khan and Thomas (2008))
α	0.25	CRS production, isoelastic demand with 33% markup
ν	0.5	CRS labor share of 2/3, capital share of 1/3
ρ^A	0.95	Quarterly persistence of aggregate productivity (Khan and Thomas (2008))
ρ^Z	0.95	Quarterly persistence of idiosyncratic productivity (Khan and Thomas (2008))
<i>Adjustment Costs</i>		
δ_k	2.6%	Annual depreciation of capital stock of 10%
δ_n	8.8%	Annual labor destruction rate of 35% (Shimer (2005))
F^K	0	Fixed cost of changing capital stock (Bloom (2009))
S	33.9%	Resale loss of capital in % (Bloom (2009))
F^L	2.1%	Fixed cost of changing hours in % of annual sales (Bloom (2009))
H	1.8%	Per worker hiring/firing cost in % of annual wage bill (Bloom (2009))

^aThe model parameters relating to preferences, technology, and adjustment costs are calibrated as referenced above.

4.1. Calibration

Frequency and Preferences

We set the time period to equal a quarter. The household's discount rate, β , is set to match an annual interest rate of 5%. The variable η is set equal to 1, which implies that the momentary utility function features an elasticity of intertemporal substitution of 1 (i.e., log preferences in consumption). Following [Khan and Thomas \(2008\)](#) and [Bachmann, Caballero, and Engel \(2013\)](#), we assume that $\chi = 1$. This assumption implies that we do not need to forecast the wage rate in addition to the forecast of p in our Krusell–Smith algorithm, since the household's labor optimality condition with $\chi = 1$ implies that the wage is a function of p alone. We set the parameter θ such that households spend about a third of their time working in the nonstochastic steady state.

Production Function, Depreciation, and Adjustment Costs

We set δ_k to match a 10% annual capital depreciation rate. Based on [Shimer \(2005\)](#), we set the annual exogenous quit rate to 35%. We set the exponents on capital and labor in the firm's production function to be $\alpha = 0.25$ and $\nu = 0.5$, consistent with a capital cost share of 1/3 of total input costs.

As previously discussed, the existing literature provides a wide range of estimates for capital and labor adjustment costs. We use adjustment cost parameters from [Bloom \(2009\)](#). The resale loss of capital amounts to 34%. The fixed cost of adjusting hours is set to 2.1% of annual sales, and the hiring and firing costs equal 1.8% of annual wages.

Aggregate and Idiosyncratic TFP Processes

Productivity, both at the aggregate and the idiosyncratic level, is determined by AR(1) processes as specified in equations (2) and (3). The serial autocorrelation parameters ρ^A and ρ^Z are set to 0.95, similar to the quarterly value used by [Khan and Thomas \(2008\)](#).

4.2. Estimation

The Uncertainty Process

We assume that the stochastic volatility processes, σ_t^A and σ_t^Z , follow a two-point Markov chain:

$$\sigma_t^A \in \{\sigma_L^A, \sigma_H^A\}, \quad \text{where } \Pr(\sigma_{t+1}^A = \sigma_j^A | \sigma_t^A = \sigma_k^A) = \pi_{k,j}^{\sigma^A}, \quad (19)$$

$$\sigma_t^Z \in \{\sigma_L^Z, \sigma_H^Z\}, \quad \text{where } \Pr(\sigma_{t+1}^Z = \sigma_j^Z | \sigma_t^Z = \sigma_k^Z) = \pi_{k,j}^{\sigma^Z}. \quad (20)$$

Since we cannot directly observe the stochastic process of uncertainty in the data, we proceed with SMM estimation. We formally discuss in Appendix C the estimation procedure and all relevant details.

Since the empirical results in Section 2 suggested that microeconomic and macroeconomic uncertainty co-move through the business cycle, we assume that a single process determines the economy's uncertainty regime. That is, our assumption of a single uncertainty process implies that whenever microeconomic uncertainty is low (or high), so is macroeconomic uncertainty. This assumption reduces the number of parameters governing the uncertainty process to six: σ_L^A , σ_H^A , σ_L^Z , σ_H^Z , $\pi_{L,H}^{\sigma}$, and $\pi_{H,L}^{\sigma}$.

As the uncertainty process has a direct impact on observable cross-sectional and aggregate time-series moments, it is natural that the SMM estimator minimizes the sum of

TABLE V
ESTIMATED UNCERTAINTY PARAMETERS^a

Quantity	Estimate	Standard Error	
σ_L^A	0.67	(0.098)	Quarterly standard deviation of macroproductivity shocks (%)
σ_H^A/σ_L^A	1.6	(0.015)	Macrovolatility increase in high uncertainty state
σ_L^Z	5.1	(0.807)	Quarterly standard deviation of microproductivity shocks (%)
σ_H^Z/σ_L^Z	4.1	(0.043)	Microvolatility increase in high uncertainty state
$\pi_{L,H}^\sigma$	2.6	(0.485)	Quarterly transition probability from low to high uncertainty (%)
$\pi_{H,H}^\sigma$	94.3	(16.38)	Quarterly probability of remaining in high uncertainty (%)

^aThe uncertainty process parameters are structurally estimated through an SMM procedure (see the main text and Appendix C in the Supplemental Material). The estimation process targets the time-series moments of the cross-sectional interquartile range of the establishment-level shock to estimated productivity in the Census of Manufactures and Annual Survey of Manufactures manufacturing sample, along with the time-series moments of estimated heteroskedasticity of the U.S. aggregate Solow residual based on a GARCH(1, 1) model. Both sets of target moments from the data are computed from 1972 to 2010.

squared percentage deviations of the following eight model and U.S. data moments: At the microeconomic level, we target the (i) mean, (ii) standard deviation, (iii) skewness, and (iv) autocorrelation of the time series of the cross-sectional interquartile range of establishment TFP shocks computed from our annual Census sample covering 1972–2010. At the macrolevel, we target the same four moments based on the time series of estimated heteroskedasticity using a GARCH(1, 1) model for the annualized quarterly growth rate of the U.S. Solow residual, covering 1972Q1–2010Q4. We display the estimated uncertainty process parameters in Table V and the targeted moments in Table VI.

Based on this estimation procedure, we find that periods of high uncertainty occur with a quarterly probability of 2.6%. The period of heightened uncertainty is estimated to be persistent with a quarterly probability of 94% of staying in the high uncertainty state. Aggregate volatility is 0.67% with low uncertainty and increases by approximately 60% when an uncertainty shock arrives. Idiosyncratic volatility is estimated to equal 5.1% and

TABLE VI
UNCERTAINTY PROCESS MOMENTS^a

	Data	Model
<i>Macro-moments</i>		
Mean	3.36	3.58
Standard deviation	0.76	0.59
Skewness	0.83	1.18
Serial correlation	0.88	0.83
<i>Micro-moments</i>		
Mean	39.28	38.44
Standard deviation	4.89	4.55
Skewness	1.16	0.81
Serial correlation	0.75	0.65

^aThe microdata moments are calculated from the U.S. Census of Manufactures and Annual Survey of Manufactures sample using annual data from 1972–2010. Microdata moments are computed from the cross-sectional interquartile range of the estimated shock to establishment-level productivity, in percentages. The model micro-moments are computed in the same fashion as the data moments, after correcting for measurement error in the data establishment-level regressions and aggregating to annual frequency. The macrodata moments refer to the estimated heteroskedasticity from 1972–2010 implied by a GARCH(1, 1) model of the annualized quarterly change in the aggregate U.S. Solow residual, with quarterly data downloaded from John Fernald’s website. The model macro-moments are computed from an analogous GARCH(1, 1) estimation on simulated aggregate data. All model results are based on a simulation of 1000 firms for 5000 quarters, discarding the first 500 periods.

it increases by approximately 310% in the heightened uncertainty state. Table V reports the point estimates and standard errors from the SMM estimation procedure. As the table shows, most of these parameters are estimated precisely. However, in Section 5.2.3, we discuss the robustness of our numerical results to modification of each of these six parameters.

It is useful at this point to explain the large estimated increase in underlying fundamental microeconomic uncertainty σ_t^Z on the impact of an uncertainty shock in light of the apparently more muted fluctuations of our microeconomic uncertainty proxy in Figure 3. Although closely related and informative for one another, the two series are distinct. Crucially, as we discuss in detail in our estimation Appendix C, the process of constructing our cross-sectional data proxy for microeconomic uncertainty involves time aggregation from quarterly to annual frequency, an unavoidable temporal mismatch of the measurement of inputs and outputs within the year, as well as measurement error of productivity in the underlying Census of Manufactures sample. In Appendix C, we demonstrate within the model that each of these measurement steps leads to a reduction in the variability of the uncertainty proxy relative to its mean level, with the temporal mismatch between input and output measurement, as well as measurement error itself, accounting for the bulk of the shift. The large increase in microeconomic uncertainty σ_t^Z , which we estimate upon impact of an uncertainty shock, is critical for matching the behavior of measured productivity shock dispersion in the data. As Table VI demonstrates, the estimated model quite closely captures the overall time-series properties of measured uncertainty in our data.

5. QUANTITATIVE ANALYSIS

In what follows, we explore the quantitative implications of our model. We begin by discussing the unconditional second moments generated by the model. We then continue by specifically studying the effects of an uncertainty shock.

5.1. Business Cycle Statistics

Table VII illustrates that the model generates second-moment statistics that resemble their empirical counterparts in U.S. data. We simulate the model over 5000 quarters using the histogram or nonstochastic simulation approach following Young (2010). We then compute the standard set of business cycle statistics, after discarding an initial 500 quarters. As in the data, investment and hours co-move with output. Output and consumption co-move, although not as much as in the data. Investment is more volatile than output, while consumption is less volatile. Given the high assumed Frisch elasticity of labor supply, the model also generates a realistic volatility of hours relative to output. See Rogerson (1988), Hansen (1985), or Benhabib, Rogerson, and Wright (1991) for a discussion of underlying mechanisms that can generate more elastic labor supply in this class of models. Overall, we conclude that the business cycle implications of our model are consistent with the common findings in the literature.

5.2. The Effects of an Uncertainty Shock

As has been known since at least Scarf (1959), nonconvex adjustment costs lead to Ss investment and hiring policy rules. Firms do not hire and invest until productivity reaches an upper threshold (the S in Ss), and do not fire and disinvest until productivity hits a lower threshold (the s in Ss). This is shown for labor in Figure 5, which plots the distribution of firms by their productivity/labor ratios, $\frac{Az}{n-1}$, after the micro- and macro-shocks have

TABLE VII
BUSINESS CYCLE STATISTICS^a

	Data			Model		
	$\sigma(x)$			$\sigma(x)$		
	$\sigma(x)$	$\sigma(y)$	$\rho(x, y)$	$\sigma(x)$	$\sigma(y)$	$\rho(x, y)$
Output	1.6	1.0	1.0	2.0	1.0	1.0
Investment	7.0	4.5	0.9	11.9	6.0	0.9
Consumption	1.3	0.8	0.9	0.9	0.4	0.5
Hours	2.0	1.3	0.9	2.4	1.2	0.8

^aThe first panel contains business cycle statistics for quarterly U.S. data covering 1972Q1–2010Q4. The term $\sigma(x)$ is the standard deviation of the log variable, $\sigma(y)$ is the standard deviation in log variable relative to the standard deviation of log output, and $\rho(x, y)$ is the correlation of the log variable and log output. All business cycle data are current as of July 14, 2014. Output is real gross domestic product (FRED GDPC1), investment is real gross private domestic investment (GPDIC1), consumption is real personal consumption expenditures (PCECC96), and hours is total nonfarm business sector hours (HOANBS). The second panel contains business cycle statistics from unconditional simulation of the estimated model, computed from a 5000-quarter simulation with the first 500 periods discarded. All series are HP-filtered with smoothing parameter 1600, in logs expressed as percentages.

been drawn but before firms have adjusted. On the right is the firm-level hiring threshold (right solid line) and on the left the firing threshold (left solid line), in the case of low uncertainty. Firms to the right of the hiring line will hire, firms to the left of the firing line will fire, and those in the middle will be inactive for the period. An increase in uncertainty increases the returns to inaction, shown by the increased hiring threshold (right dotted line) and reduced firing threshold (left dotted line). When uncertainty is high, firms become more cautious as labor adjustment costs make it expen-

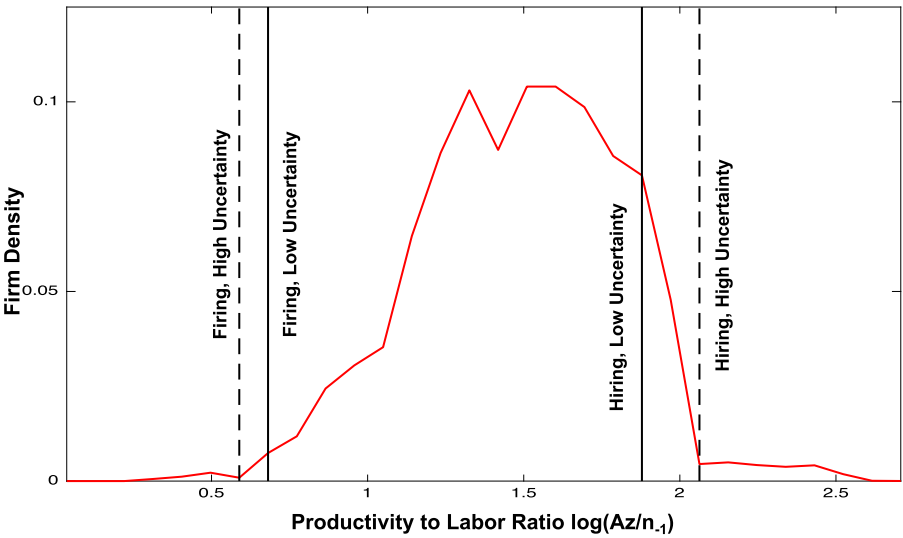


FIGURE 5.—The impact of an increase in uncertainty on the hiring and firing thresholds. Notes: The figure plots the simulated cross-sectional marginal distribution of micro-level labor inputs after productivity shock realizations and before labor adjustment. The distribution plots a representative period with average aggregate productivity and low uncertainty levels. The vertical hiring and firing thresholds are computed based on firm policy functions with average micro-level productivity realizations, taking as given the aggregate state of the economy with low uncertainty (solid lines) and a high uncertainty counterfactual (dotted lines).

sive to make a hiring or firing mistake. Hence, the hiring and firing thresholds move out, increasing the range of inaction. This leads to a fall in net hiring, since the mass of firms is right-shifted due to labor attrition. A similar phenomenon occurs with capital, whereby increases in uncertainty reduce the amount of net investment.

5.2.1. *Modelling a Pure Uncertainty Shock*

To analyze the aggregate impact of uncertainty, we independently simulate 2500 economies, each of 100-quarter length. The first 50 periods are simulated unconditionally, so all exogenous processes evolve normally. Then for each economy, after 50 quarters, we insert an uncertainty shock by imposing a high uncertainty state. From the shock period onward each economy evolves normally. To calculate the impulse response function to an uncertainty shock for any macrovariable, we first compute the average of the aggregate variable in each period t across simulated economies. The effect of an uncertainty shock is then simply given by the percentage deviation of the average in period t from its value in the pre-shock period.

Figure 6 depicts the impact of an uncertainty shock on output. For graphical purposes, period 0 in the figure corresponds to the pre-shock period in the above discussion, that is, quarter 50. Figure 6 displays a drop in output of just over 2.5% within one quarter. This significant fall is one of the key results of this paper as it shows that uncertainty shocks can be a quantitatively important contributor to business cycles within a general equilibrium framework. A quick recovery follows the initial decline, and output returns to normal levels within 1 year. We note that output then declines again moderately from quarters 6 onward. We defer the discussion for the intuition behind this result until Section 5.2.4.

These dynamics in output arise from the dynamics in three channels: labor, capital, and the misallocation of factors of production. These are depicted in Figure 7. First, in

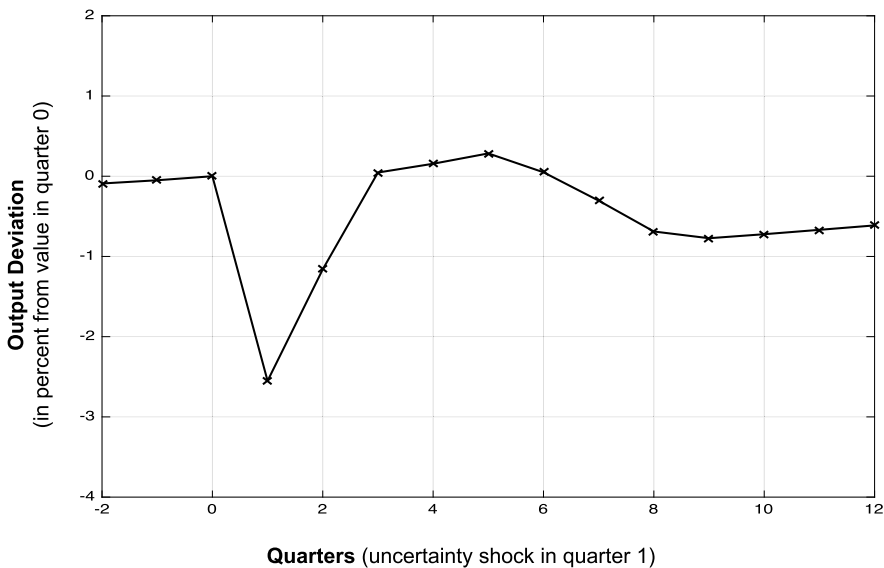


FIGURE 6.—The effects of an uncertainty shock. Notes: Based on independent simulations of 2500 economies of 100-quarter length. We impose an uncertainty shock in the quarter labelled 1, allowing normal evolution of the economy afterwards. We plot the percent deviation of cross-economy average output from its value in quarter 0.

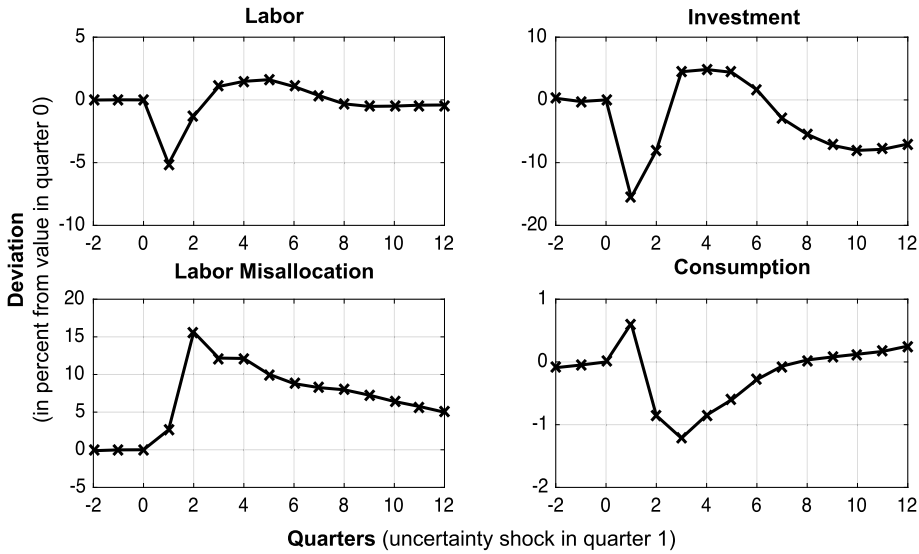


FIGURE 7.—Labor and investment drop and rebound, misallocation rises, and consumption overshoots then falls. Notes: Based on independent simulations of 2500 economies of 100-quarter length. We impose an uncertainty shock in the quarter labelled 1, allowing normal evolution of the economy afterwards. Clockwise from the top left, we plot the percent deviations of cross-economy average labor, investment, consumption, and the dispersion of the marginal product of labor from their values in quarter 0.

the top-left panel, we plot the time path of hours worked. When uncertainty increases, most firms pause hiring, and hours worked begin to drop because workers are continuing to attrit from firms without being replaced. In the model, this rate of exogenous attrition is assumed to be constant over the cycle. This is consistent with [Shimer \(2005\)](#) and [Hall \(2005\)](#), who show that around three-quarters of the movements in the volatility of unemployment are due to job-finding rates and not to the cyclical of the destruction rate. Similarly, in the top-right panel, we plot the time path of investment, which drops rapidly due to the increase in uncertainty. Since investment falls but capital continues to depreciate, there is also a drop in the capital stock.

Misallocation of factor inputs—using the terminology of [Hsieh and Klenow \(2009\)](#)—increases in the economy in response to an uncertainty shock. In normal times, unproductive firms contract and productive firms expand, helping to maintain high levels of aggregate productivity. But when uncertainty is high, firms reduce expansion and contraction, shutting off much of this productivity-enhancing reallocation. In the bottom-left panel, we plot the path of the dispersion of the marginal product of labor after an uncertainty shock. More precisely, the bottom-left panel plots the impulse response of the cross-sectional standard deviation of $\log(\frac{y}{n})$. In the wake of an uncertainty shock, labor misallocation endogenously worsens, improving only slowly. In the longer run, labor, investment, misallocation, and output all start to recover to their steady state, as the uncertainty shock is temporary. As uncertainty falls back, firms start to hire and invest again to address their pent-up demand for labor and capital. In Figure B3 in the Supplemental Material, we depict alternative measures of misallocation. As Figure B3 shows, all of these alternative measures point to the same result of increased misallocation following an uncertainty shock.

In the lower-right panel of Figure 7, we plot the time profile of consumption. When the uncertainty shock occurs, consumption jumps up in the first quarter before subsequently

falling back below the mean of the ergodic distribution for several quarters. The logic behind this initial increase in consumption is as follows. In the impact period of the uncertainty shock, that is, period 1 in Figure 7, the households understand that the degree of misallocation has increased in the economy as the bottom-left panel demonstrates. Increased misallocation acts as a negative first-moment shock to aggregate productivity and thus lower the expected return on savings, making immediate consumption more attractive and thus leading to its first-period increase. Furthermore, this jump in consumption is feasible since, in the impact period of the uncertainty shock, the freeze in both investment and hiring reduces the resources spent on capital and adjustment costs, thus freeing up resources. After this initial jump, starting in period 2 in Figure 7, the capital stock is now below its ergodic distribution, where we note that in the impact period of the uncertainty shock, the pre-shock aggregate capital level was fixed. This fact, together with hours worked being below their ergodic distribution and the degree of misallocation being above its ergodic distribution, limits the overall resources in the economy and thus limits consumption. In addition, the economy begins its recovery in period 2 in Figure 7, which is manifested in investment and hiring beginning to increase relative to the values exhibited during the impact period of the uncertainty shock. This recovery requires resources to be spent on capital and adjustment costs, further reducing the available resources for consumption. Interestingly, we note that [Khan and Thomas \(2013\)](#) find in their model of credit constraints that while output, labor, and investment fall in response to a credit tightening shock, in fact consumption, as in our model, also initially rises due to similar general equilibrium effects.

Clearly, this rise in consumption at the start of recessions is an unattractive feature of a pure uncertainty shock model of business cycles. Several options exist, however, to try and address this. One is to allow consumers to save in other technologies besides capital, for example, in foreign assets. This is the approach [Fernandez-Villaverde et al. \(2011\)](#) take in modelling risk shocks in small open economies. In an open economy model, a domestic uncertainty shock induces agents to increase their savings abroad (capital flight). In our closed model this is not possible, but extending the model to allow a foreign sector would make this feasible, although computationally more intensive. Another option would be to use utility functions such as those in Greenwood, Hercowitz, and Huffman (1988). Due to the complementarity between consumption and hours in such preference structures, they should reduce the overshoot in consumption. We do not explore these options for the following two reasons. Having another investment vehicle such as foreign bond would add an additional state variable to the problem, and switching the preference structure would require us to forecast wages separately from marginal utility. Both changes would increase the computational burden considerably. Another option would be to model precautionary behavior from households in the wake of an uncertainty shock, as [Basu and Bundick \(2016\)](#) do in a new-Keynesian environment with demand-determined output. Such behavior would allow for natural investment, consumption, and output comovement, but expanding the aggregate structure of the model to account for nominal rigidities is beyond the scope of the current paper.

5.2.2. *First-Moment and Second-Moment Shocks*

Our quantitative results so far reveal that uncertainty shocks can contribute importantly to recessions, but there are at least two unattractive implications of modelling an uncertainty shock in isolation. First, the empirical evidence in Section 2 suggests that recessions are periods of both first- and second-moment shocks, at least to the extent that the average growth rates of TFP and output decrease and their variances increase. Second, in our

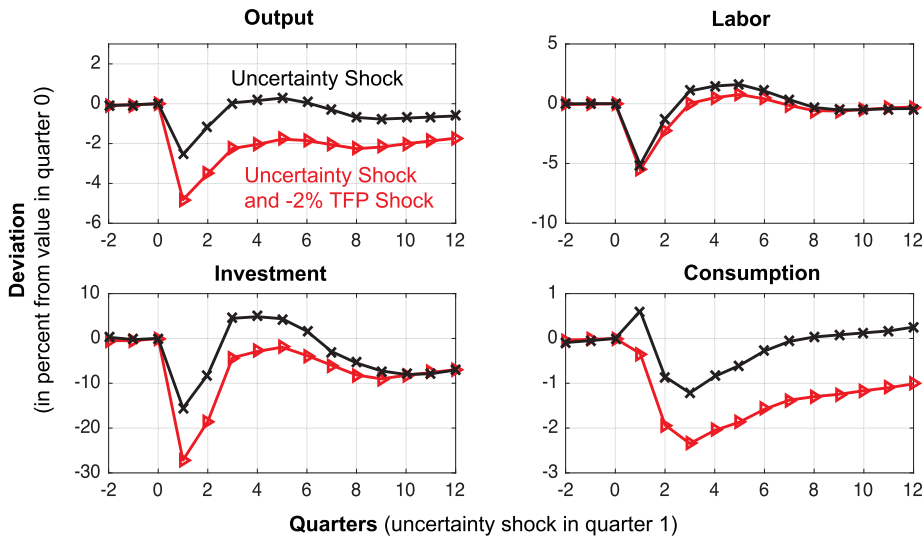


FIGURE 8.—Adding a -2% first-moment shock increases the output fall and eliminates a consumption overshoot. Notes: Based on independent simulations of 2500 economies of 100-quarter length. For the baseline (\times symbols) we impose an uncertainty shock in the quarter labelled 1. For the uncertainty and TFP shock (\blacktriangleright symbols), we also impose an aggregate productivity shock with average equal to -2% , allowing normal evolution of the economy afterwards. Clockwise from the top left, we plot the percent deviations of cross-economy average output, labor, consumption, and investment from their values in quarter 0.

model, uncertainty shocks are associated with an increase in consumption on impact and a reduction in disinvestment and firing (see Figures 5 and 7).

Thus, to generate an empirically more realistic simulation, we consider the combination of an uncertainty shock *and* a -2% exogenous first-moment shock. See Appendix B for a discussion of the specific numerical experiment considered here.

As Figure 8 suggests, this additional shock magnifies the drop in output, investment, and hours. The addition of the first-moment shock also leads to a fall in consumption on impact. Given the business cycle co-movement we observe empirically, we conclude that simultaneous first- and second-moment shocks in the model can generate dynamics that resemble recent U.S. recessions.

5.2.3. Robustness

In this section, we discuss the robustness of our finding to different parameterizations. We first consider the robustness of our results with respect to the estimated parameters governing the uncertainty process. Since the estimated values in Section 4.2 pointed to (i) a significant jump in both micro- and macro-uncertainty, (ii) a significant persistence of the uncertainty process, and (iii) a moderately high frequency of high uncertainty, we consider experiments where we reduce the values of each of these parameters. For consistency, unless otherwise noted, every robustness experiment considers a reduction of 25% in the parameter value. Thus, within this set we consider (i) a reduction of the macrovolatility jump, $\frac{\sigma_H^A}{\sigma_L^A}$, from 1.6 to 1.2, (ii) a reduction of the microvolatility jump, $\frac{\sigma_H^L}{\sigma_L^L}$, from 4.13 to 3.10, (iii) a reduction in the likelihood of transition from low uncertainty to high uncertainty, $\pi_{L,H}^\sigma$, from 0.026 to 0.02, and (iv) a reduction in the uncertainty persistence, $\pi_{H,H}^\sigma$, from 0.94 to 0.71. Finally, we also consider two additional experiments

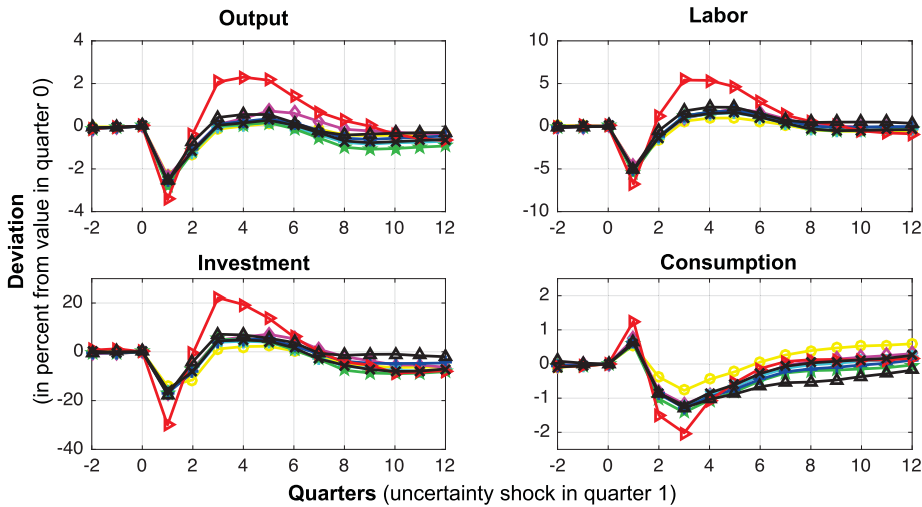


FIGURE 9.—The impact of an uncertainty shock is robust to a wide range of alternative calibrations. Notes: Based on independent simulations of 2500 economies of 100-quarter length. For all simulations we impose an uncertainty shock in the quarter labelled 1, allowing normal evolution of the economy afterwards. Baseline (\times symbols) is the estimated baseline path. Other paths plot responses assuming a reduction in low-uncertainty micro volatility (σ_L^Z , \circ symbols), the high-uncertainty increase in micro volatility (σ_H^Z/σ_L^Z , \blacklozenge symbols), low-uncertainty macro volatility (σ_L^A , $+$ symbols), the high-uncertainty increase in macro volatility (σ_H^A/σ_L^A , $*$ symbols), the frequency of an uncertainty shock ($\pi_{L,H}^\sigma$, stars), the persistence of an uncertainty shock ($\pi_{H,H}^\sigma$, \blacktriangleright symbols), all adjustment costs for labor and capital (\blacktriangle symbols). Clockwise from the top left, we plot the percent deviations of cross-economy average output, labor, consumption, and investment from their values in quarter 0.

where (i) we lower the microvolatility baseline value, σ_L^Z , from 0.051 to 0.038 and (ii) we lower macrovolatility baseline value, σ_L^A , from 0.0067 to 0.0050. Figure 9 plots the effects of each of these variations on output, investment, labor, and consumption. As Figure 9 suggests, the results are overall robust to these changes, preserving the dynamics reported in Figures 6–8. The one exception is the reduction in the persistence of the uncertainty shock to 0.7 from the estimated value of 0.94. At lower levels of persistence, the impact is short-lived. This highlights how the dynamics of the impact of uncertainty shocks are sensitive to the persistence of the underlying shock and is another motivation for our SMM estimation of the parameters of the uncertainty process. We note that the estimated value of 0.94 for the autocorrelation of uncertainty may seem high. However, this potentially accounts for the endogenous amplification of uncertainty from slower growth proposed by a range of other papers.

In addition to systematically plotting robustness checks to changes in the value of each of our six estimated uncertainty process parameters, Figure 9 also plots the results from one additional experiment in which we reduce the value of all capital and labor adjustment cost parameters by 25% simultaneously. The effect of an uncertainty shock changes little relative to our baseline, a result that reflects the fact, well known within the literature on investment and adjustment costs, that the sizes of inaction regions are concave functions of adjustment costs. For example, see the analytical results in Dixit (1995) and Abel and Eberly (1996) that show that the size of the inaction region for investment in their models expands to the third or fourth order in adjustment costs around zero.

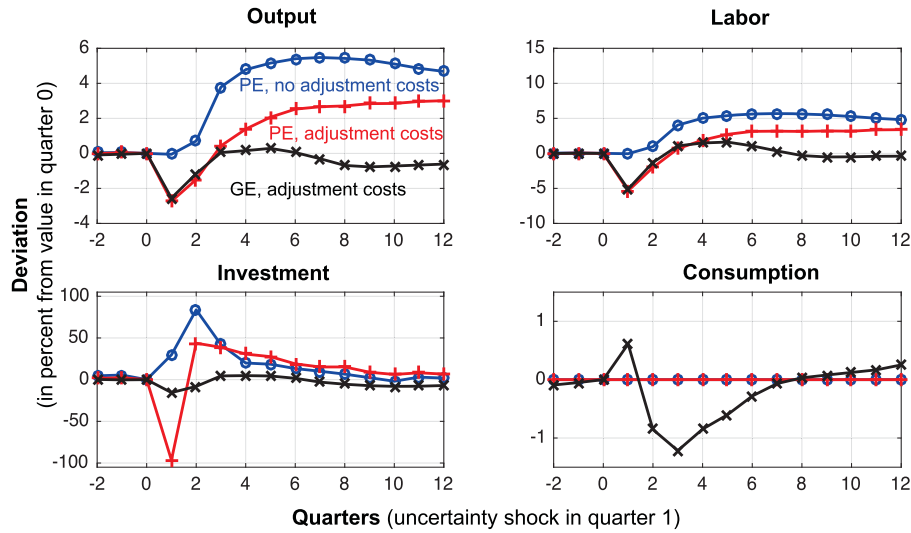


FIGURE 10.—The impact of an uncertainty shock combines Oi–Hartman–Abel, real options and consumption smoothing effects. Notes: Based on independent simulations of 2500 economies of 100-quarter length. For all simulations we impose an uncertainty shock in the quarter labelled 1, allowing normal evolution of the economy afterwards. GE, adjustment costs (× symbols) is the baseline, and the PE responses are partial equilibrium paths with adjustment costs (+ symbols) and without adjustment costs (o symbols). Clockwise from the top left, we plot the percent deviations of cross-economy average output, labor, consumption, and investment from their values in quarter 0. Note that PE economies have no consumption concept, with deviations therefore set to 0.

5.2.4. *Decomposing the Impact of Uncertainty*

The next set of robustness results studies how the effects of uncertainty shocks differ across general equilibrium (GE) and partial equilibrium (PE) frameworks. To address this question, we plot in Figure 10 the impact of an uncertainty shock in three different economies. The line with × symbols depicts again the effects of an uncertainty shock in our GE model economy, the line with + symbols depicts the same response but with PE only (all prices and wages are held constant and the consumer side of the economy is ignored), while the line with o symbols depicts the effects of an uncertainty shock in a PE economy with no adjustment costs at all. Note that in the bottom-right panel in the PE economies, consumption is not defined because there is no notion of an aggregate household. We therefore impose a zero response path for consumption in those cases.

When there are no adjustment costs of any type in a PE economy, output actually increases following an uncertainty shock. The reason for this result is related to the Oi (1961), Hartman (1972), and Abel (1983) effect, whereby a higher variance of productivity increases investment, hiring, and output because the optimal capital and labor choices are convex in productivity.

By contrast, the addition of adjustment costs to the PE setup dramatically changes the effect of an uncertainty shock. Now, on impact there is a fall in aggregate output. The reason is that the increase in uncertainty moves firms’ labor and capital *S*s bands out, temporarily pausing hiring and investment. If all firms pause hiring and investment, aggregate labor and capital drop due to labor attrition and capital depreciation. But this pause is short-lived, as once uncertainty drops back, firms start to hire and invest again.

So in the medium run, the Oi–Hartman–Abel effect dominates and output rises above its long-run trend.

While these forces are also present in the baseline GE adjustment cost economy, the curvature in the utility function, that is, the endogenous movement in the interest rate, moderates the rebound and overshoot. The overshoot in the PE economy requires big movements in investment and labor, which are feasible since consumption is not taken into account in the PE framework. However, in the GE framework, the curvature in utility slows down the rebound of the GE economy, generating a smoother and more persistent output cycle. Intriguingly, in the first period, however, GE has very little impact on output relative to the PE economy with adjustment cost. This is because the S s bands have moved so far out that there is a reduced density of firms near the hiring or investment thresholds to respond to prices. Hence, the short-run robustness of the impact of uncertainty shocks to GE suggested by Bloom (2009) seems to be present, while the medium-run sensitivity to GE highlighted by Thomas (2002) and Khan and Thomas (2003, 2008) is also present.

We are now in position to discuss the reason for the sluggish behavior of output in the medium term after an uncertainty shock in Figure 6. First, on impact in periods 1 and 2, the “real options” effect due to the uncertainty shock dominates, leading to a hiring/investment freeze, misallocation, and, thus, a significant drop in output. Later on in periods 3–5, the economy exhibits a “rebound” as the high microvolatility is realized and some firms draw significantly higher productivity shocks than before. Firms start to readjust and the Oi–Hartman–Abel effect leads to a recovery. During the third stage starting in periods 6–8, output declines again.

Two factors play a role in the second fall in output. First, the level of misallocation remains high, which acts as a drag on output and is a large contributor to the slowdown of the recovery. The bottom-left panel of Figure 7 reveals that the cross-sectional dispersion of the marginal product of labor—a measure of labor misallocation—remains almost 10% higher in period 6 and declines only slowly as firms begin to adjust their inputs again in the wake of an uncertainty shock. Underlying misalignment of inputs and productivity at the microlevel prevents effective use of the capital and labor stock of the aggregate economy, and meaningful input adjustment costs prevent such misallocation from resolving itself quickly over this period.

The second factor contributing to the second more gradual decline in output is a declining path for investment starting around period 6. By this stage, the real options effect has subsided in large part and the economy has a low but growing consumption path. This results in a declining path of interest rates over which it is optimal to have a declining investment path. These investment dynamics of the economy in the third stage of the response to an uncertainty shock resemble those that show up in a basic neoclassical growth model as in Brock and Mirman (1972). Figure D1 in the Supplemental Material plots the response of such an economy to a capital destruction shock. As the figure shows, consumption converges from below at a declining rate, and investment declines over the path.

5.2.5. *Laws of Motion Robustness*

Our final set of robustness checks studies the impact of variations in the labor and capital depreciation rates. In these experiments we vary one by one the capital depreciation rate and the labor depreciation rate by one quarter each. The results are depicted in Figure 11. As the figure suggests, unsurprisingly reduction of the labor depreciation rate attenuates the fall in hours and thus in output but preserves the overall dynamics found in the benchmark calibration. Changes in the capital depreciation rate do not change the fall

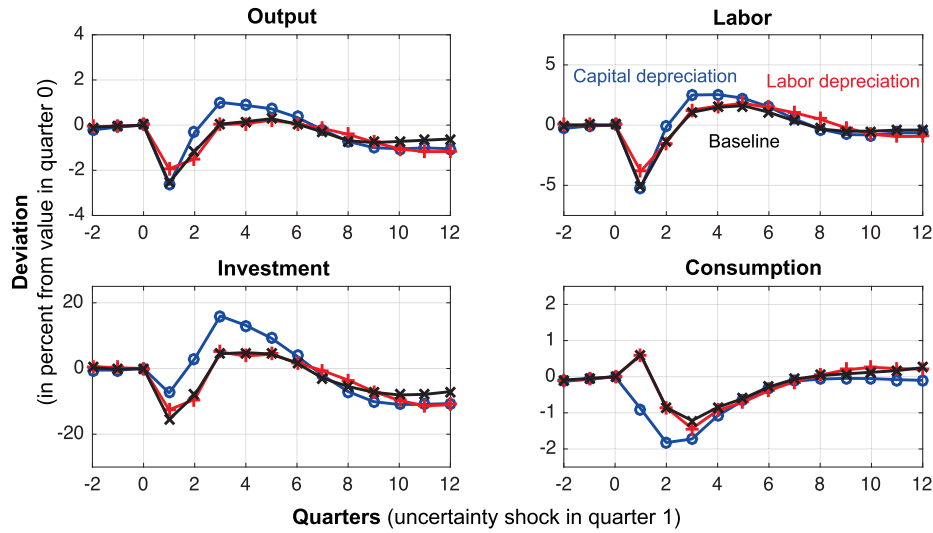


FIGURE 11.—The impact of an uncertainty shock is reduced by lower rates of capital depreciation or labor attrition. Notes: Based on independent simulations of 2500 economies of 100-quarter length. For all simulations we impose an uncertainty shock in the quarter labelled 1, allowing normal evolution of the economy afterwards. Baseline (× symbols) is the estimated baseline path. The two other paths plot responses assuming a 25% reduction in the capital depreciation rate (o symbols) and labor depreciation rate (+ symbols). Clockwise from the top left, we plot the percent deviations of cross-economy average output, labor, consumption, and investment from their values in quarter 0.

on impact, which is driven by the behavior in labor. Later on, a lower capital depreciation rate accentuates the recovery from an uncertainty shock as it induces a strong rebound in investment leading to an increase in capital and thus in labor and output. However, we note that the more empirically relevant exercise is to *increase* the capital depreciation rate, since investment is increasingly shifting toward intangible areas, which have much higher depreciation rates. For example, the Bureau of Economic Analysis’s (BEA) migration of R&D from the satellite accounts to the fixed assets tables is based on depreciation rates of around 20% or higher (Li (2012)). Thus, while the reduction in annual depreciation does reduce the impact of an uncertainty shock, the empirically relevant depreciation rate in the economy is likely much higher.

6. POLICY IN THE PRESENCE OF UNCERTAINTY

In this section, we analyze the effects of stimulative policies in the presence of uncertainty shocks. It is important to emphasize that any such policy is *not* optimal within the context of our model, as the competitive equilibrium is Pareto optimal. Rather, we see our policy experiments as a means to document and quantify the effects of such policies in times of heightened uncertainty. It is also worth noting that this ignores the direct impact of policy on uncertainty as studied by papers such as Baker, Bloom, and Davis (2016) and Hassan, Hollander, van Lent, and Tahoun (2017).

The policy experiment we consider is a policy that attempts to temporarily stimulate hiring by reducing the effective wage paid by firms. More specifically, the policy consists of an unanticipated 1% wage bill subsidy paid for one quarter and financed through a lump-sum tax on households. We simulate this policy impulse once during an uncertainty shock and also in an economy that is not hit by an uncertainty shock. By comparing the

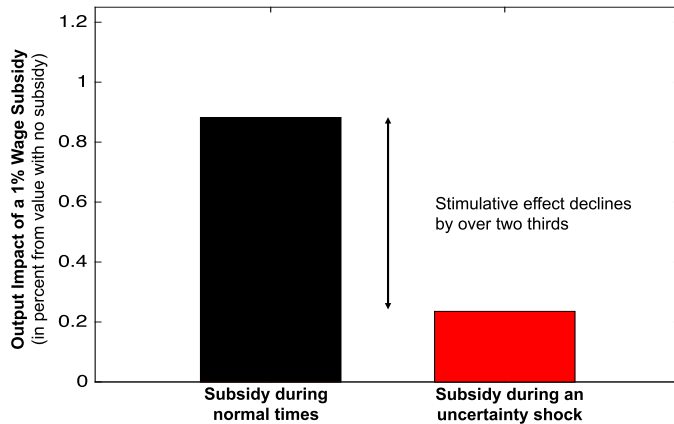


FIGURE 12.—Policy is less effective in the aftermath of an uncertainty shock. Notes: Based on independent simulations of 2500 economies of 100-quarter length. For a wage subsidy in normal times (black bar, left), we provide an unanticipated 1% wage bill subsidy to all firms in quarter 1, allowing the economy to evolve normally thereafter. We also simulate an economy with no wage subsidy in quarter 1. The bar height is the percentage difference between the cross-economy average subsidy and no subsidy output paths in quarter 1. For the wage subsidy with an uncertainty shock (red bar, right), we repeat the experiment but simultaneously impose an uncertainty shock in quarter 1.

marginal effect in those two cases, we attempt to identify the effect of uncertainty on policy effectiveness.

Figure 12 depicts this experiment as it shows the net impact of the policy. That is, we first solve for the effects of the policy on output when it *does not* coincide with an uncertainty shock. Subtracting from this the behavior of output when there is no uncertainty shock and no subsidy yields the net impact of the policy in the absence of an uncertainty shock. We then solve for the policy's effect when it *does* coincide with an uncertainty shock. Similarly, subtracting from this latter experiment the behavior of output when there is an uncertainty shock and no subsidy, the behavior depicted in Figure 6 yields the net impact of the policy in the presence of an uncertainty shock. As Figure 12 shows, the presence of uncertainty reduces the effects of the wage policy by over two-thirds on impact. The reason is that as soon as uncertainty rises, the S_s thresholds jump out, so many firms are far away from their hiring and investment thresholds, making them less responsive to any policy stimulus. Our results here echo findings from the lumpy investment literature on the procyclicality of the investment response to productivity shocks (e.g., [Bachmann, Caballero, and Engel \(2013\)](#)). In particular, we show that uncertainty or second-moment shocks in addition to first-moment shocks can also generate movement in the responsiveness of the economy to shocks. Interestingly, in the context of a new-Keynesian economy with a distinct structure and policy experiment, [Vavra \(2014\)](#) also finds that second-moment shocks reduce the responsiveness of the economy to policy.

Overall, our results highlight how uncertainty shocks lead to time-varying policy effectiveness. At the instant an uncertainty shock hits, policy is not as effective relative to normal times. Hence, uncertainty shocks not only impact the economy directly, but also indirectly change the response of the economy to any potential reactive stabilization policy.

7. CONCLUSIONS

Uncertainty has received substantial attention as a potential factor in business cycles. The first part of this paper uses Census microdata to show that measured uncertainty is indeed strongly countercyclical. This is true both at the aggregate and the industry level: slower industry growth is associated with higher industry uncertainty.

The second part of the paper then builds a DSGE model with heterogeneous firms, time-varying uncertainty, and adjustment costs to quantify the impact of second-moment shocks. We find that uncertainty shocks typically lead to drops of about 2.5% in GDP, with a sharp drop, quick recovery, and then continued sluggishness in output. This suggests that uncertainty could play an important role in driving business cycles, either as an impulse or amplification mechanism. We also find that because uncertainty makes firms cautious, the response of the economy to stimulative policy substantially declines. Finally, both our empirical and simulation results suggest recessions are best modelled as a combination of a negative first-moment and a positive second-moment shock.

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